that vildagliptin 50 mg bid and sitagliptin 100 mg qd are equivalent is 99.3%. The result of a sensitivity analysis showed that the probability of the two drugs remaining equivalent remains high (>90%) over a wide range of MCIDs. **CONCLUSIONS:** This innovative method has the potential to improve understanding of equivalence (or non-inferiority) between drugs for multiple stake-holders.

PRM204

PROPERTIES OF PROPENSITY SCORE MATCHING PROCEDURES ON COVARIATE BALANCING AND ESTIMATION: INFLUENCE OF THE NUMBER OF PROPENSITY SCORE DIGITS USED ON MATCHED SETS CREATED

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OBJECTIVES: Applying propensity scores from confounders and their interactions, we observed the effect of reducing the number of digits for propensity score matching including resulting outcome point estimates. **METHODS:** We included sex, race, education, marital status, census region, year, age, insurance, and all pair-wise interactions for a 7 digit propensity score quantifying the conditional probability of low income status. Using 10 years of Medical Expenditure Panel Survey data, we assessed the association of low income status and experiencing an emergency room visit. We incrementally reduced matched propensity score digits from 7 to 2, observing effects on sample size, standardized differences in confounders, differences in covariate variance, odds ratio [OR] estimates, and Akaike Information Criterion [AIC]. **RESULTS:** Generally, fewer matching digits exacerbated differences in confounders between the matched sets. However, six digit matching was superior to seven-digit matching in confounder differences (standardized differences [SD] of 0 versus .01 respectively) as was 3 digit versus 4 digit matching (SD of 3.39 versus 3.99 respectively). The pattern of variance differences was identical to the SD differences. Sample size was largest with 2 digit matching (n=80,624), progressively diminishing with each additional digit matched (7 digit matching had n=61,168). AIC inflated inversely with digit reduction: 47,298.99 for 7 digit matching and 63,660.528 for 2 digit matching. ORs were consistent throughout (smallest OR=1.355 with 4 digits and largest OR=1.386 with 6 digits). **CONCLUSIONS:** Propensity score matching seeks to minimize differences between exposure groups. When propensity scores are generated using interaction terms, matching on a greater number of digits may not produce a better matched set of exposed and unexposed groups in terms of confounders. Analysts must consider the mechanism in which propensity scores are produced when specifying the matching algorithm.

PRM205

GENERATING DISTRIBUTIONS AND DATA: EVALUATING ONLINE, FREEWARE OPTIONS FOR HEALTH ECONOMIC MODELS

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OBJECTIVES: To evaluate an online, freeware JavaScript program that can be utilized in the generation and graphical illustration of alternative distributions and generate raw data for exploring cost effectiveness models. For this evaluation, beta, gamma and normal distributions were compared for a web-based resource. **METHODS:** For evaluation, we compared the results between jStat.org and R statistical software. jStat is intended as a code library written in JavaScript that allows one to perform advanced statistical operations without the need of more resource intensive software (such as MS Excel or R). The jStat graphic and plotting functionality is based on the jQuery Flot plugin. **RESULTS:** Analysis of a mix of distributions from jStat (n = 100) versus R (n=100) found the following summary of results for the two-sample Kolmogorov-Smirnov test. Beta distributions (alpha = 8, beta = 2): (medians: 0.807 vs. 0.819) D = 0.16, p-value = 0.549; gamma distributions (shape = 5, scale = 5): (medians: 23.5 vs. 26.9) D = 0.11, p-value = 0.581; and normal distributions (mean = 100, stdev = 10): (medians: 101.6 vs. 101.3) D = 0.13, p-value = 0.366. **CONCLUSIONS:** jStat is designed to perform in most major browsers and operating systems. jStat applies complicated statistical functions that may be slower with handheld processors. There are a growing number of calculators on the internet that utilize JavaScript and java for the generation and plotting of such datasets. R and MS Excel remain popular and powerful resources that are frequently used in economic analyses and modeling that includes the generation of datasets with various statistical distributions. jStat may be useful for generating and examining pilot data or exploring the health economic ramifications of a clinical publication when the full patient dataset is not readily available.

PRM206

METHODOLOGICAL CHALLENGES IN THE ESTIMATION OF THE INCIDENCE RATE OF RARE DISEASES FROM SPECIALIZED CENTERS: LESSONS LEARNED FROM A STUDY OF MULTICENTRIC CASTLEMAN'S DISEASE

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OBJECTIVES: Studies that estimate incidence of very rare diseases (less than 1 in 100,000 of the general population) often use cases seen at specialized centers. However, multiple potential sources of both systematic error and random error complicate this estimation. We calculated the incidence rate of Multicentric Castleman's Disease (MCD) based on data from two specialized centers. Our objective is to describe the main challenges of incidence estimation of rare diseases in general, and specifically of MCD, and to suggest how to improve the assessment accuracy. **METHODS:** All the patients that were newly diagnosed with MCD at 2 centers were included. Patients' locations were identified from the first 3 digit of their zip codes and mapped using a Geographical Information system (GIS). Catchment areas for each center were defined based on spatial patterns and center-specific clinician input. CENSUS data were used to estimate the size of the reference population and to calculate the crude and stratified incidence rates. **RESULTS:** Uncertainty resulted from small sample size; center-specific population features and referral patterns; under-diagnosis and difficulty of diagnosis; association between disease risk factors and proximity to the centers; and difficulty with defining a catchment area to establish the relevant population denominator. Analysis involved a trade-off between the number of patients included in a catchment area and catchment area definition, with clearer geographical boundaries that maximized the proportion of MCD patients in the population represented in the center. **CONCLUSIONS:** Small sample sizes in combination with multiple potential sources of error challenge an accurate estimate of incidence. Finer definitions of each center catchment area further reduce the number of included cases but can improve the accuracy of the incidence estimate.

PRM207

DISEASE EXPENDITURE MODELS AND CALIBRATION METHODS ON PHYSICIAN SURVEYS

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OBJECTIVES: the research aims to design and develop cost senstivity simulators both with intention and effective data on impact of economics on decision points in clinical practices. At this point mainly drug treatment and some diagnostic decisions with lab tests have been investigated. This step deals with a milestone to move from static to dynamic econometric modeling for reliable physicians's cost awareness estimates on how patients 'economic influence decisions, at the point of visits, for labtests and treatment decisions; by investigating various sources of changes in the survey. **METHODS:** several calibration issues are investigated following the first series of runs with the Physician National Ambulatory Medicare Survey. The analytical data sets used have been designed on diabetes, hypertension and asthma. Populations are identified with ICD codes, drug lists are also used to ascertain the population under study. Drug treatments are identified with drug codes, originally from the NDC and generic codes; the successive analytical datasets extracted from the NAMCS physician survey are used to estimate reliable estimates on impact of insurance and payment/billing systems, controlling for changes due to drug codes, ICD classification, categorization of patients, stages of computerization of EHRs, including reports on lab and diagnostic tests. **RESULTS:** The test of the dynamic modeling to adjust over time the disease models will lead to a synopsis of the different results from studies initiated since 2003. Comparison of results across three diseases already demontrate the consistency of the effects of the selected variables on insurance and payment or billing. It allows to identify conditions of replicability of the survey designs and to quantify the scope of biases. **CONCLUSIONS:** This stage of development will lead to propose reliable adjustement methods to integrate the various changes affecting the physician survey and the constitution of reliable analytical datasets extracted from that survey on major chronic conditions.

PRM208

LANDMARK ANALYSIS TO ADJUST FOR IMMORTAL TIME BIAS IN ONCOLOGY STUDIES USING CLAIMS DATA LINKED TO DEATH DATA

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OBJECTIVES: Immortal time bias (ITB), the inclusion of person-time during which the study outcome cannot occur, has been shown to bias study findings. We examine the impact of ITB by estimating the effect of chemotherapy on overall survival, and demonstrate how landmark analysis can correct the bias. **METHODS:** Retrospective study using the MarketScan® Research Databases with commercially and Medicare insured individuals linked to the Social Security Administration Death records. Subjects with newly diagnosed metastatic breast cancer (ICD-9-CM 174.x plus additional codes 196.xx-199.xx) and ≥1 year of continuous enrollment prior to breast cancer diagnosis were identified. Chemotherapy exposure was defined as ≥3 chemotherapy claims following metastatic cancer diagnosis. Landmark analysis was used to estimate survival rates conditional on surviving to certain time points to adjust for ITB. Time to death or censoring was determined for the full sample and patients who survived 1, 3, 6 and 12 months. **RESULTS:** A total of 5759 metastatic breast cancer patients were identified of which 2932 had ≥3 claims for chemotherapy during follow-up. Average survival time for chemotherapy patients was 9.0 months longer than patients with <3 chemotherapy claims. The difference in survival times between patients with and without chemotherapy decreased as patients were required to survive for longer periods of time: 1-month survival = +8.9 months, 3-month survival = +7.0 months, 6-month survival = +6.7 months, 12-month survival = +7.0 months. The artificially increased effect of chemotherapy in the full sample analysis was due to the time between metastatic cancer diagnosis and third chemotherapy claim being "immortal" for the chemotherapy patients (median 2.6 months). **CONCLUSIONS:** Landmark analysis can be used to account for immortal time bias in oncologystudies analyzing the effect of new treatments or the comparative effectiveness of current treatments. However, an appropriate landmark must be chosen as results can be affected.